How to assess the robustness of a flexible transport using an Agent Based Model?

Adrien Lammoglia, Nicolas Marilleau, Didier Josselin

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Comment évaluer la robustesse d'un service de transport flexible simulé en Système Multi-Agent ?

Some observations on optimal conditions of simulation.

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Abstract
This paper presents a method to evaluate the robustness of a cooperating flexible transport system based on agents (taxis and clients) and simulated using NetLogo. Analysing a set of 124 scenarios of simulations on a range of synthetic populations (clients) and on various space networks organizations, we assess the sensitivity of a transportation model we proposed. Our main objective is to detect robustness thresholds in flow configurations and system efficiency. The research leads to two main results: (i) there exists an optimal balance between the frequency of system iterations (number of clients generations) and the total number of clients involved in simulations, (ii) to some extend, the network topological structure plays a non negligible role in transport efficiency.

Résumé
Cet article présente une méthode pour évaluer la robustesse d'un service de transport flexible modélisé en multi-agent et simulé sur la plate-forme Netlogo. Nous analysons la sensibilité du modèle grâce à 124 scénarios de simulation, chacun d'eux intégrant différentes quantités de population synthétique (les clients), combinées à quatre formes d'organisation spatiale théoriques.Notre objectif est de révéler des seuils de robustesse au delà desquels le système peut être considéré comme efficace ou non. À l'aide de plusieurs indicateurs, nous montrons qu'il existe un ratio optimal entre la fréquence et la quantité de client à créer. Nous expliquons aussi dans quelle mesure la forme des réseaux routiers influence l'efficacité du modèle.

Keywords

Agent Based Model; flexible transport; robustness; model evaluation; sensitivity analysis

Mots clés
Système Multi-Agent; transport flexible; robustesse; évaluation de modèle; analyse de sensibilité

1. Introduction

This proposition aims at defining a method to assess the flexible transport robustness using an approach related to model validation and verification. After having given a few definitions of the experimental context, we shall detail the application in flexible transport modelling and then provide a set of results including statistical analysis.

1.1. Flexible transport

Flexibility is a concept widely developed in complex system science and operational research (Billaut *et al.*, 2005). It has many facets. A flexible transport is a public or private transportation service, whose schedules and routes can vary according to immediate client needs (Castex, 2007). Flexibility depends on the kind of service operating: a regular line activated with at least a single client, up to a fleet of responsive taxis which define their routes on the fly, according to random reservations. A flexible transport must be able to adapt to different (i) needs of mobility, (ii) different types of spatial network configurations, (iii) technological and financial constraints of clients and carriers. There exist indeed several types of flexible transport. For instance, Demand Responsive Transports (DRT) (Castex & Josselin, 2007), in spite of their capacity to adapt to a varying mobility demand, are organized by a high level authority (the 'management center of mobility') which optimizes vehicle routes according to different criteria. On a more individual level, vehicles can behave in co-operation or competition in order to satisfy the mobility needs. For example, this kind of service is observed in Africa, in the city of Dakar, by different taxi corporate bodies and some non corporate services (taxis ‘clandos’) (Godard, 2002; Cervero & Golub, 2007).

1.2. Robustness and model sensitivity

Robustness is a methodological purpose. A clue or an estimator is considered as robust when (i) it can only be affected by a large set of little deviations, or by (ii) a little quantity of large deviations from the theoretical law or to the experienced data distribution (Hoaglin *et al* 1983; Hampel *et al.*, 1986). In the case of transportation, this means the system can remain stable and efficient when some 'outlier' demand occur. A transport can be considered as robust when it ensures a good quality of service, by resisting to mobility demand fluctuation, in real time. We propose to extend this definition to transportation model validation. In this particular case, it becomes possible to tune some criteria while others remain stable and to figure out some thresholds over which the transport efficiency falls. This process is often used to assess the sensitivity of the system to disruption (Drezner, 1986; Labbé *et al.,* 1990; Querriau *et al.,* 2004). From the exploration of model parameters (number or frequency of generated clients), we can provide a generalized study of the system sensitivity). We estimate the influence of key parameters on the system efficiency, and define the conditions for getting an efficient virtual transport system.

1.3. Model validation and verification

Model validation and verification (V&V) should take an essential place in complex system modeling (Bommel, 2009). V&V intends to ensure: (i) the model reliability, (ii) truth of scientific hypothesis assumed during the modeling process and (iii) model representativeness according to the complex system studied. V&V is a key process to give confidence to a model (Sargent, 2010). Nevertheless, this is often reduced to the simplest process: a few experiments are chosen and applied to reproduce an identified dynamic and to promote the model. It is generally due to the lack of data extracted from the complex system. In addition, V&V is time consuming and needs some technical skills, sometimes unavailable for modelers.

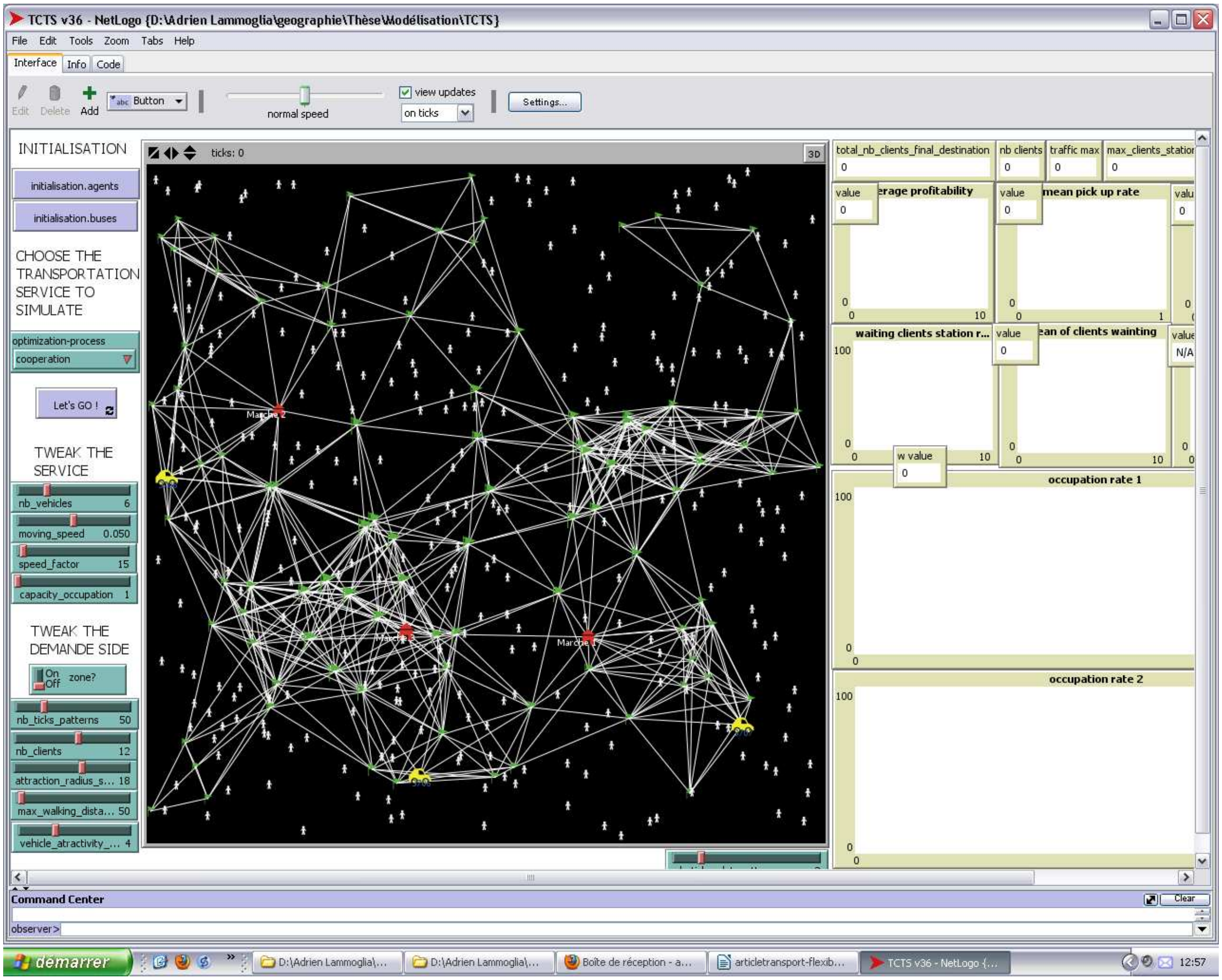
Validation and Verification are performed during the modeling process. First, verification checks or proves that the model complies scientist modeling specifications (Brocard, 2008). Due to the complexity of the studied systems and their unpredictable behavior at a microscopic level, it seems hopeless to give a proof ensuring the correctness of a model. Despite this statement, the validation intends to analyse the model, to experience it to ensure that it gives a response to the scientific question (Petty, 2009). Therefore, many experiments must be done to explore the model parameters.

Agent Based Models (ABM) is indeed a powerful approach for modeling mobility systems (Meister *et al.*, 2010). By identifying agents behavior, it enables to simulate various flexible transports, to monitor and to analyse a global service functioning. It becomes then possible, using simulations, to accurately follow along the mobility system, according to a set of pertinent statistical parameters (Lammoglia, 2011). The characteristics of the complex system and the scientific lead this exploration: a running ordered process and several parameter values are fixed according to distinct assumptions. That is the way we proceed.

1.4. Issue and implementation of a flexible DRT

In our virtual DRT experiments, transport efficiency bases on several components to be assessed: (i) evolution of clients quantity, (ii) road network and (iii) spatial distribution of urban places of interest. Many geo-computation algorithms and methods for simulating and optimizing DRTs have been provided in the literature as mentioned in several papers (Garaix *et al.* 2011, 2007, Chevrier *et al.* 2008). In our case, there is no optimization kernel and we propose to focus on cooperating agents behavior to assess how robust can be a flexible transport. Thence, we apply V&V method to evaluate the robustness of a theoretical and simulated transport. The model has been implemented and simulated using the NetLogo Multi-Agent System (MAS) (fig.1) (Ferber, 1995 ; Tisue & Wilensky, 2004 ; Amblard & Phan, 2006). We performed many simulations, according to a series of virtual client quantities, several road network patterns and a suitable set of statistical indicators of efficiency (e.g. 3.2.).

Figure 1: The platform of simulation



2. Application od Validation and verification on flexible transport simulation

2.1. A model for simulating flexible transport

To describe and to explain how the model operates, we first propose to use the standard ODD protocol (Grimm *et al.*, 2006; Grimm et *al.*, 2010).

2.1.1. Purpose

From a K.I.S.S. ("Keep it simple and short") model, we have developed an Agent-Based Model (ABM) reproducing demand transport system. The main objective of this ABM is to evaluate the ability of cooperating taxis to respond to a spontaneous and non organized demand-side of mobility. Throughout hundreds simulations, we want to exhibit and evaluate transportation strategies. For that, we test the efficiency of the virtual transport servicing, using statistical clues and visual analysis of spatial patterns.

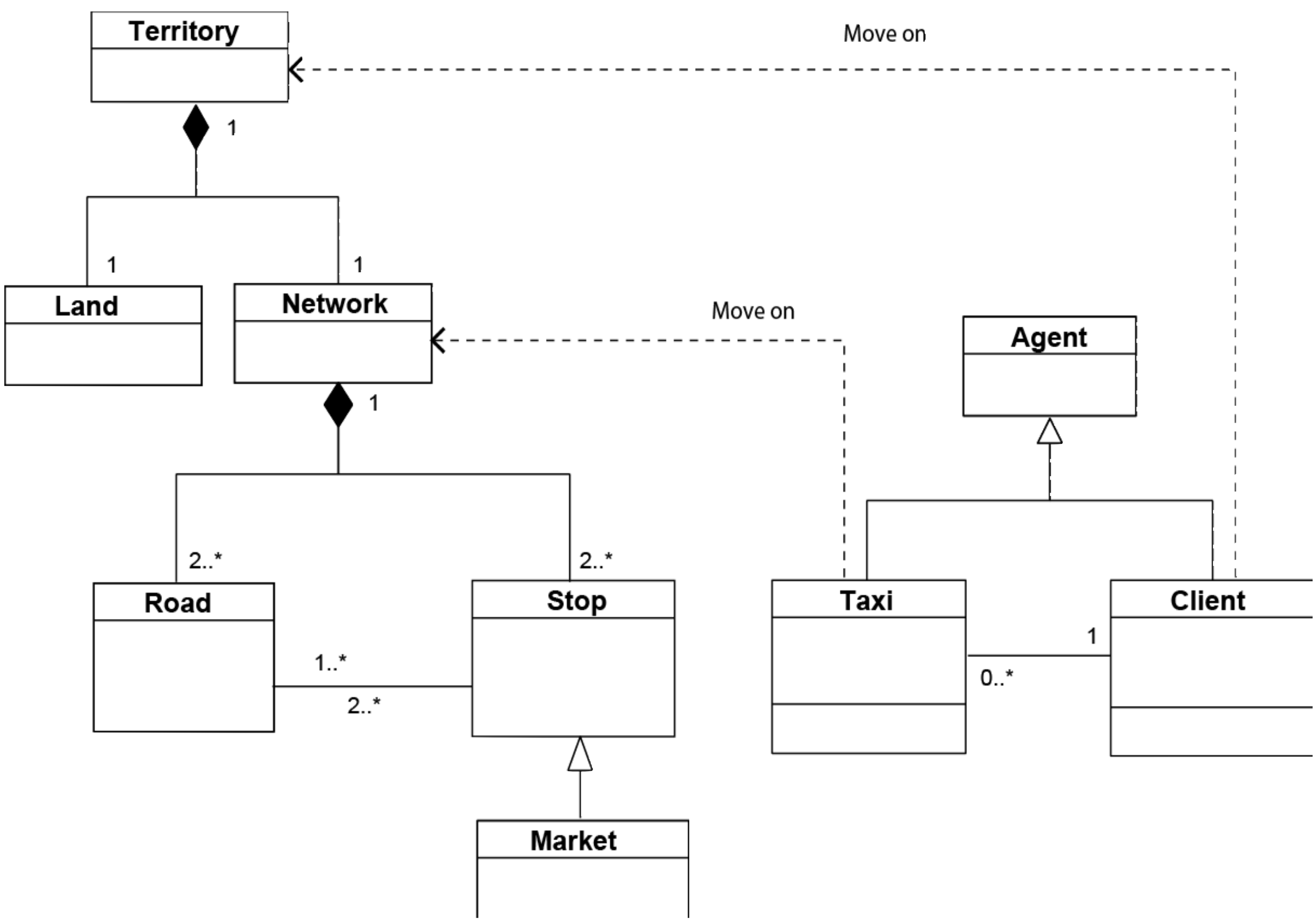
Due to our theoretical objectives, the KISS oriented modeling approach, and the number of simulation we have to do, we chose the Netlogo (Wilensky & Rand, 2013) framework to design and develop our model because: (i) it is a simple way to develop a KISS agent-based model; (ii) a large community used this plateform; (iii) it can be used by scientific who have a short experience in computer sciences; (iv) Netlogo contains features to automize model exploration, the behavior space toolbox.

2.1.2. Entities, state variables and scales

As we can see in the class diagram (fig. 2), we distinguish two species of individuals: clients and taxis. Each species is modeled by a population of agents (one agent per individual). Agents of a species are qualified with the same behavior. Nevertheless, they are differentiated by their limited knowledge about the network, their location and the transportation system. Agents move on a virtual network made up of continuous land and a road network. To evaluate the efficiency of the virtual transport on a given spatial configuration, we designed four different theoretical networks (e.g. 3.1.). For each of them, the graph is non planar, not complete, not directed. Stops (where taxis can pick up clients) and markets (where clients want to go) are vertices or nodes of the edges of the network.

The model (without space and time measure unit) is focused on pickup and delivery strategies of taxi. All simulations run during 15 000 time steps (time units in major ABM) because the process often converges beyond 5 000 steps although it may change a little during the last 10 000 steps.

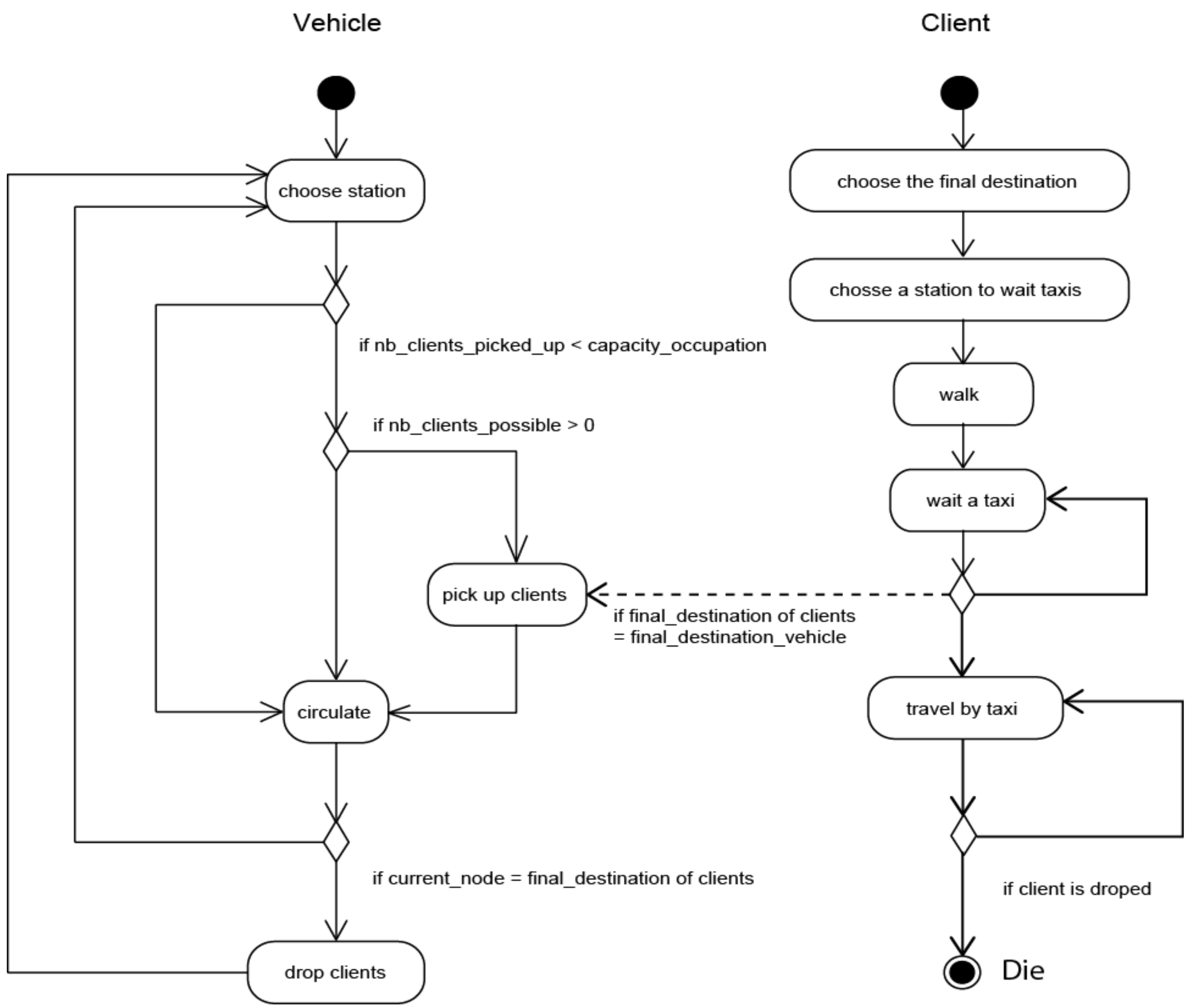
Figure 2: Class diagram of the flexible transport model



2.1.3. Agent behaviour overview

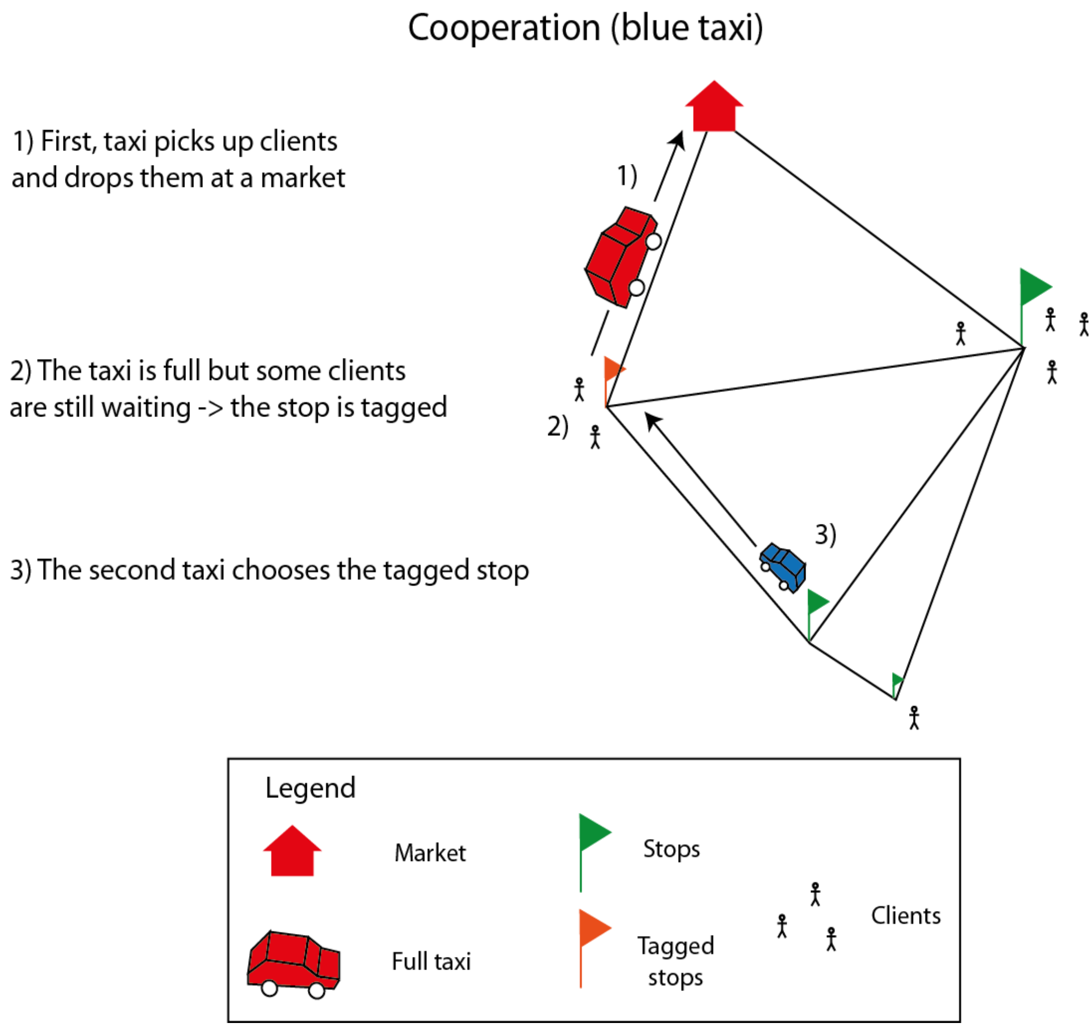
Along the network, taxis continuously move from stops to stops and pick up clients to carry them to a market. Clients are randomly and regularly generated in a constant quantity. Pedestrians wait at a stop station to take a taxi to reach a market. After their generation, they walk to the most attractive and the closest stop. Next, they catch a taxi and they are "satisfied" when they arrive at the market (fig. 3).

Figure 3: Activity diagram of the agents



In our experiments, the transport service involves only 3 taxis and each taxi can carry a maximum of 10 clients. When these taxis pick up clients and if there are still some clients waiting, they transmit the information to all the other taxis, using marks on certain stops, as insects let pheromones on their paths (fig. 4). Taxis randomly move on the network and foremost target these tagged stops. The section 2.1.7 provides more details about agent behavior with coding examples.

Figure 4: Cooperation process between taxis



2.1.4. Design concepts

Basic principles: (i) Clients target the most attractive stops and markets by using a sort of gravity model measured by the potential of attractiveness (depending on the frequenting of stops and markets), divided by the euclidean distance between the clients and the stops. The potential of attractiveness of each stop is added during the routing process and depends on routes frequency. More visited the stop by agents, more attractive.

(ii) Taxis communicate and cooperate using an optimization principle of pheromone as in the ant colony algorithm (Dorigo *et al.*, 2006). Once a taxi has picked up clients at a given stop and if there are still some clients waiting at the stop, the taxi tags the stop. Thus other taxis foremost target this stop.

Emergence: During the simulation, the spatial structure evolves and emerges, according to agents journeys. Road width is drawn proportionally to the flows of taxis. The stop and market sizes are also proportional to the number of vehicles and client visits. So at the end of the simulations, we can observe the most frequented roads and the most attractive stops and markets.

Objectives: Each type of agents owns a single objective: clients want to reach the most attractive market and taxis want to pick up the maximum of clients.
Sensing: Clients can feel the attractiveness of stops and markets. Taxis can target the tagged stops.
Interactions: There is no direct interaction between clients and taxis, but clients and taxis interact when they meet at a stop. They deal about their destination: if the taxi is empty, it picks up clients who have a common destination. Otherwise it picks up the client(s) who share its own destination.
Stochasticity: Clients are randomly and regularly generated in a constant quantity during the simulation. Taxis move randomly on the road network, except when one or more stops are tagged.
Observation: For each simulation, we export a data base from Netlogo. The *.csv files contains the values of taxi variables and the values of each indicator recorded for all iterations.

2.1.5. Initialization

We defined 124 scenarios of simulation. For all the simulations, parameters are previously fixed, such as the number of taxis (3), the maximum capacity of taxis (10 clients), the number of stops (100) and the number of markets (3). Some parameters can vary: number and frequency of clients generated during the simulation, spatial distribution of stops and markets. The scenarios are precisely described in the third part of the paper.

2.1.6. Input data

Because we use scenarios in simulating, there is no input in this model, *i.e.* parameters do not vary during the simulation and the model is completely reset before each simulation.

2.1.7. Details: optimization processes

In this last section, we explain the two major optimization processes of the model. Two algorithms respectively define how taxis and clients choose stops to move on the network.

Taxis process

NetLogo code	Explanation
to choix-noeud-cooperation [ifelse empty? list-stations-villageois-restant [let na noeud-actuel set noeud-actuel noeud-suivant set noeud-suivant one-of [link-neighbors] of noeud-actuel while [noeud-suivant = na] [set noeud-suivant one-of [link-neighbors] of noeud-actuel] let ns noeud-suivant ask noeud-actuel [ask link-with ns [set traffic-brut (traffic-brut + 1)]]] [let na noeud-actuel set list-stations-villageois-restant sort-by [[distance myself] of ?1 < [distance myself] of ?2] list-stations-villageois-restant let station-a-desservir first list-stations-villageois-restant set noeud-actuel noeud-suivant set noeud-suivant min-one-of [link-neighbors] of noeud-actuel [distance station-a-desservir] let ne max-one-of [link-neighbors] of noeud-actuel [distance station-a-desservir] while [noeud-suivant = na] [set noeud-suivant one-of [link-neighbors] of noeud-actuel] if noeud-suivant = station-a-desservir and destination-marche-taxis = 0 [set list-stations-villageois-restant remove-item 0 list-stations-villageois-restant] let ns noeud-suivant ask noeud-actuel [ask link-with ns [set traffic-brut (traffic-brut + 1)]]]] [let na noeud-actuel let dest destination-marche-taxis set noeud-actuel noeud-suivant set noeud-suivant min-one-of [link-neighbors] of noeud-actuel [distance dest] let ns noeud-suivant while [noeud-suivant = na] [set noeud-suivant one-of [link-neighbors] of noeud-actuel] ask noeud-actuel [ask link-with ns [set traffic-brut (traffic-brut + 1)]]] set nb-noeuds-passes (nb-noeuds-passes + 1) set etat 3 end	START If the taxi is empty and no stop is tagged, the taxi randomly chooses an adjoining stop. This stop is necessarily different from the previous traveled stop. Otherwise the taxi chooses the nearest tagged stop. If the taxi is already carrying clients, it chooses the nearest stop of the market. END

Clients process

Code Netlogo	Explanation
to choix-villageois-stations-marches ask villageois [if destination-marche = 0 [set destination-marche max-one-of stations with [marche? = 1] [potentiel-brut / (distance myself)] set destination-noeud max-one-of stations with [distance myself < distance-marcher-max and marche? = 0] [potentiel-brut / (distance myself)] if distance destination-noeud > distance destination-marche [set destination-noeud destination-marche]]] end	START Client chooses the market or the stop that maximizes the ratio : potential of attractivity / distance. If the stop is more distant than the market, the client directly reaches the market. END

2.2. Flexibility and robustness of the transport service

The service we simulate can be considered as flexible for two reasons. First, taxis never pre-select routes. They do not have any cognitive behavior. Secondly, they do not have any information about the client location, except when a stop is tagged. They neither have information about the number of clients generated during the simulation or waiting at the station. That is why they systematically need to check the mobility demand by randomly travelling from stop to stop. So, the system is self-organized and we analyze its performance at a global level. It is similar to the taxis fleet existing in many countries (Brazil, Senegal...) and working, for many of them, on their own.

A part of the taxi efficiency is due to their capability to communicate using tags let at certain stops, information which is then suited to the fleet. Another part of the efficiency results from the attractiveness of the most growing markets where the clients want to go. Whereas client spatial origins often differ from each others, most of time their destinations are closed. In this case, the flows of taxis are highly polarized. The robustness of such a simulated transport system is set in its capacity to properly serve the territory through the network whatever the conditions. Using a set of adequate indicators, it is possible to evaluate the efficiency variation in the simulated configurations due to some parameters changes.

3. Protocol for evaluation

3.1. Scenarios of simulation

To study the efficiency of the transport service, we simulated 124 scenarios of our system and we analyzed the variation of three main parameters of the model. All the parameters concerning the taxis are fixed (e.g. §2.1.). In parallel, the initial number of clients (from 5 to 1500) and the frequency of clients generations (from 5 to 500 iterations) can vary. After a large number of simulations, we selected

124 scenarios presented in the figure 5 to reduce simulation cost and to cover parameter range in the best way. On the one hand, it performs a scalability process, on the other hand, a progressive change of time granularity, linked to the mobility demand of moving population. To complete our analysis, we could vary the number of vehicles but such experiments are not developed in this paper.

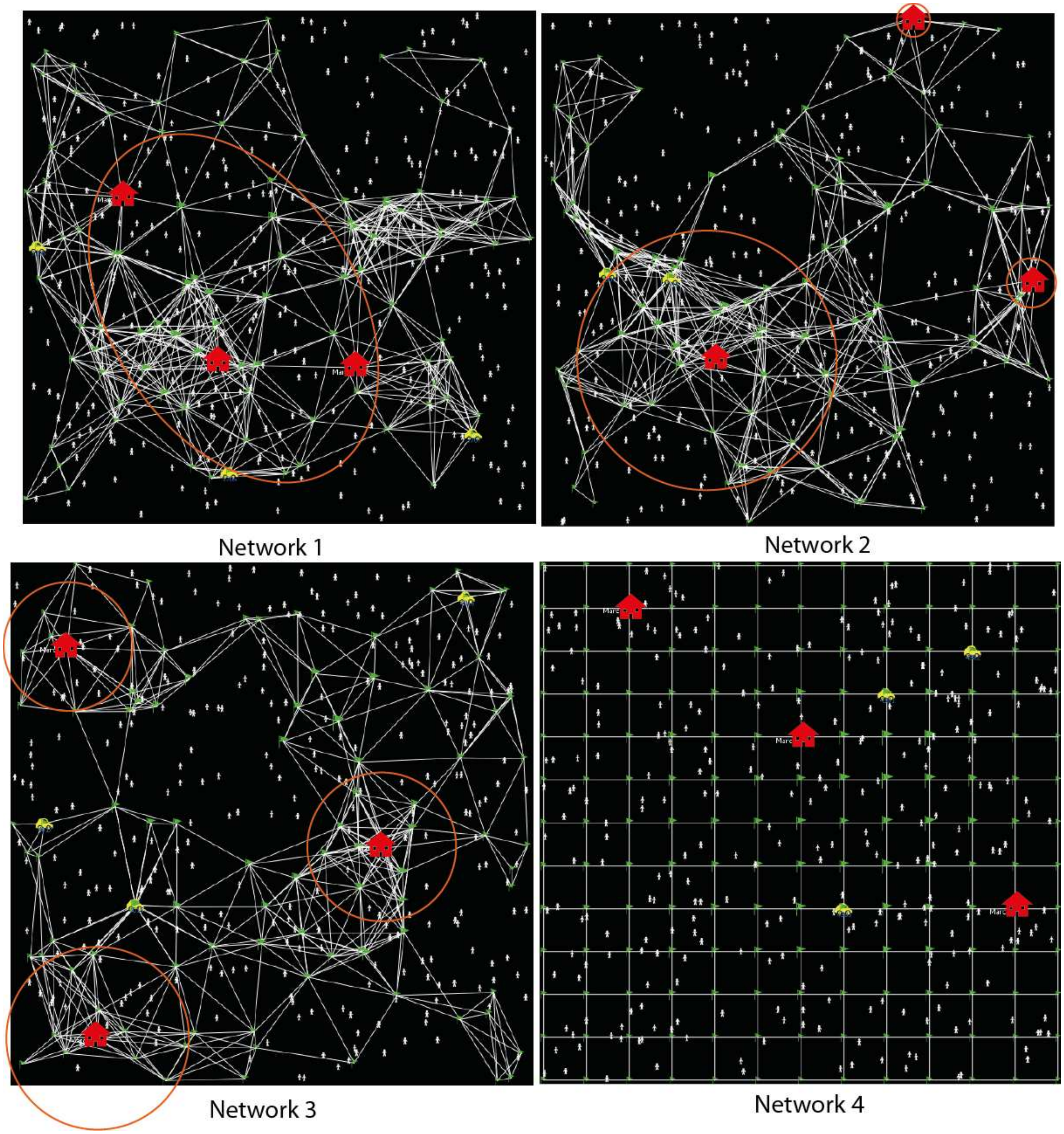
Figure 5: Matrix of client generation and simulation IDs

Number of clients created \ Frequency (iteration)	5	50	100	250	500
5	S1	S5	S9	S16	S23
10	S2	S6	S10	S17	S24
20	S3	S7	S11	S18	S25
50	S4	S8	S12	S19	S26
100			S13	S20	S27
200			S14	S21	S28
500			S15	S22	S29
1000					S30
1500					S31

This experimental plan is designed according to two main features: (i) the complex system we study and (ii) the computing power limitations. The range of frequency and clients number follows a logistic law often observed in real services. Nevertheless, the model exploration is limited by technical issues. When the number of agents simulated increases too much (around 2000), simulations slow down and freeze. It is the consequence of the NetLogo 4.0.5 limitation which is a useful framework to quickly develop models, to test hypothesis, and to change the model structures and rules. In spite it does not support large samples, Netlogo capacity is sufficient to test the tested (KISS) transport model.

Furthermore, to analyse the influence of the spatial configurations on the transportation service, we systematically simulated each combination of frequency and number of clients (see the dark squares in the figure 4) on four types of network (fig. 6). On the first network, the three markets are grouped together somewhere on space. The roads are somewhat dense on this area. For the second tested network, a market is situated on the densest area of the network and the two other markets are located on the edge of the space extent. Within the third network, we can locate three spread polarities, like three small cities. Last, the fourth configuration is a theoretical Manhattan Street Network (MSN) (Maxemchuk, 1987), showing a market in the center and two markets on the edges of the network extent. This last case is theoretical and less realistic than the three other experienced networks.

Figure 6: The four simulated networks



3.2. Indicators

In order to analyze the global performance of the service, we defined three main indicators:

- The *servicing rate* is the ratio between clients who arrived at the market and the total number of clients generated during the simulation (a high value indicates a good service efficiency) ;

- The *clients-station rate* is the proportion of clients who are waiting at a stop compared to the total number of clients generated (a low value shows a good transport efficiency) ;
- The taxi *occupancy rate* is depicted by the distribution of the number of passengers in the vehicles, processed for the whole iterations. It gives an idea of the taxi occupancy rate. A taxi can carry a maximum of ten clients. Highest the frequency in the important occupancy rates, better the service efficiency.

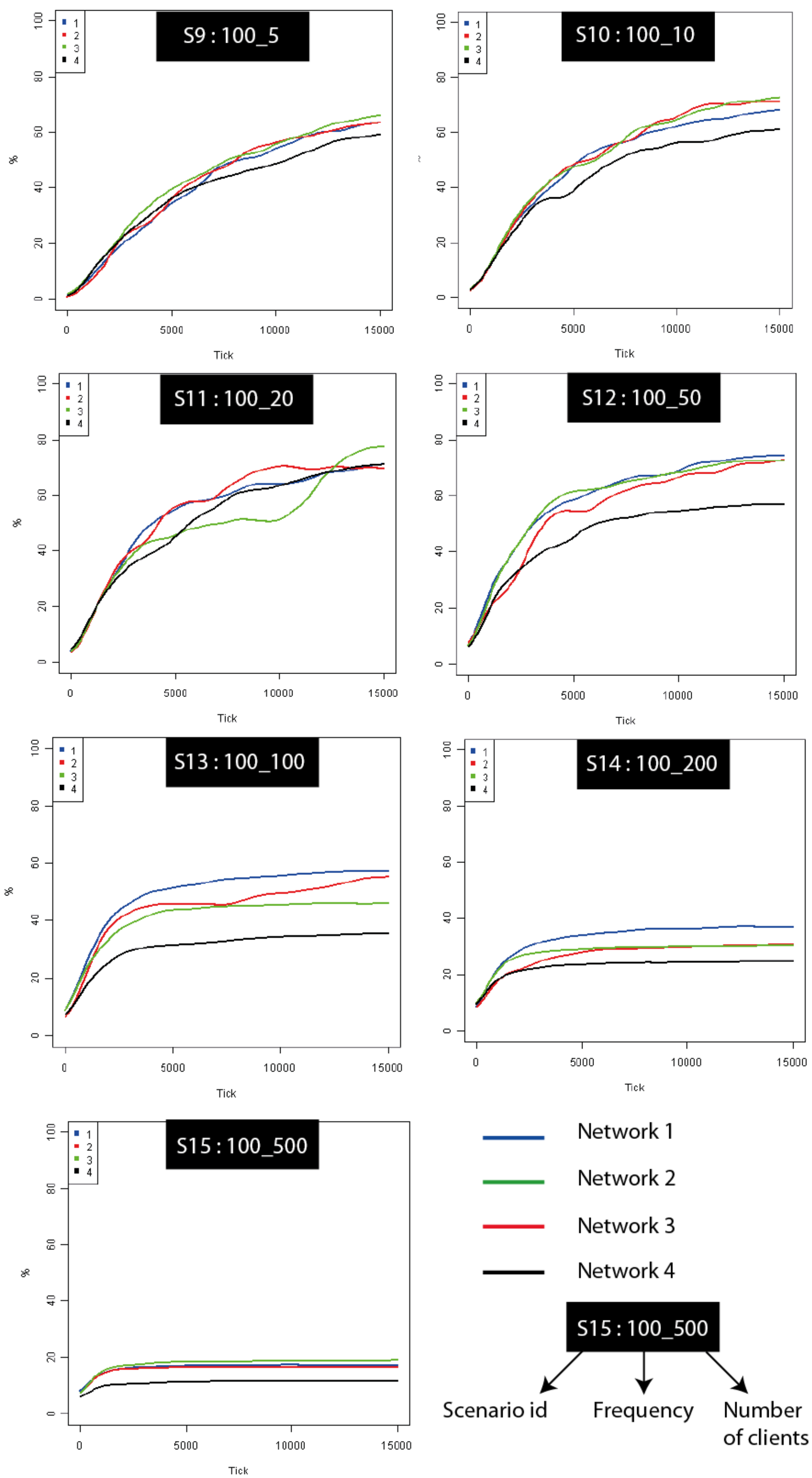
4. Statistical analysis of the simulated scenarios

For each simulated scenario, we processed four sets of plots for depicting the servicing rates, the clients-station rates and the occupancy rates (with a total of 124 plots by indicator). Sometimes statistics are gathered in a single graph to allow a comparison of transport efficiency between the 4 experienced networks.

4.1. Influence of frequency and number of clients generations

Globally, the results on monitored indicators show that the transport model is relatively sensitive to the various parameters related to the clients generation. Indeed (fig. 7), the servicing rate strongly depends on the frequency and on the number of clients initiated. For the whole simulations, the lowest value of this indicator is lower than 10% (scenario 23), whereas the best rate reaches 80% (scenario 19). The worst results concern the scenarios with extreme parameters, i.e. the scenarios either (i) with a very low quantity of clients rarely generated (for example the scenario 23 with 5 clients created every 500 iterations), or (ii) with a very high quantity of clients frequently generated (for example the scenario 4 with 50 clients created every 5 iterations). In the first case, the efficiency is weak because the density of clients is too low to fill the taxis. As taxis always travel with at most one or two clients (this is confirmed by taxi occupancy rates), operating is very slow and only a few clients arrive to a targeted market. The second case is the opposite. Too many clients are present at the same time and the taxis do not succeed in picking up them all, despite very good taxi occupancy rates. In this case, the service would need more taxis or a larger capacity of seats per vehicle. Thus, the best servicing rate obtained involves parameter intermediate values of clients generation. They range from 60% to 80% of clients arrived at a market (for example, in scenarios 9, 18, 26). There exists indeed an optimal ratio linking the taxi fleet and the demand. As the curves presented in the figure 6 show, this relevance also depends on the kind of networks and on the virtual networks which are drawn.

Figure 7: Comparison of the servicing rates for various numbers of clients generated every 100 iterations

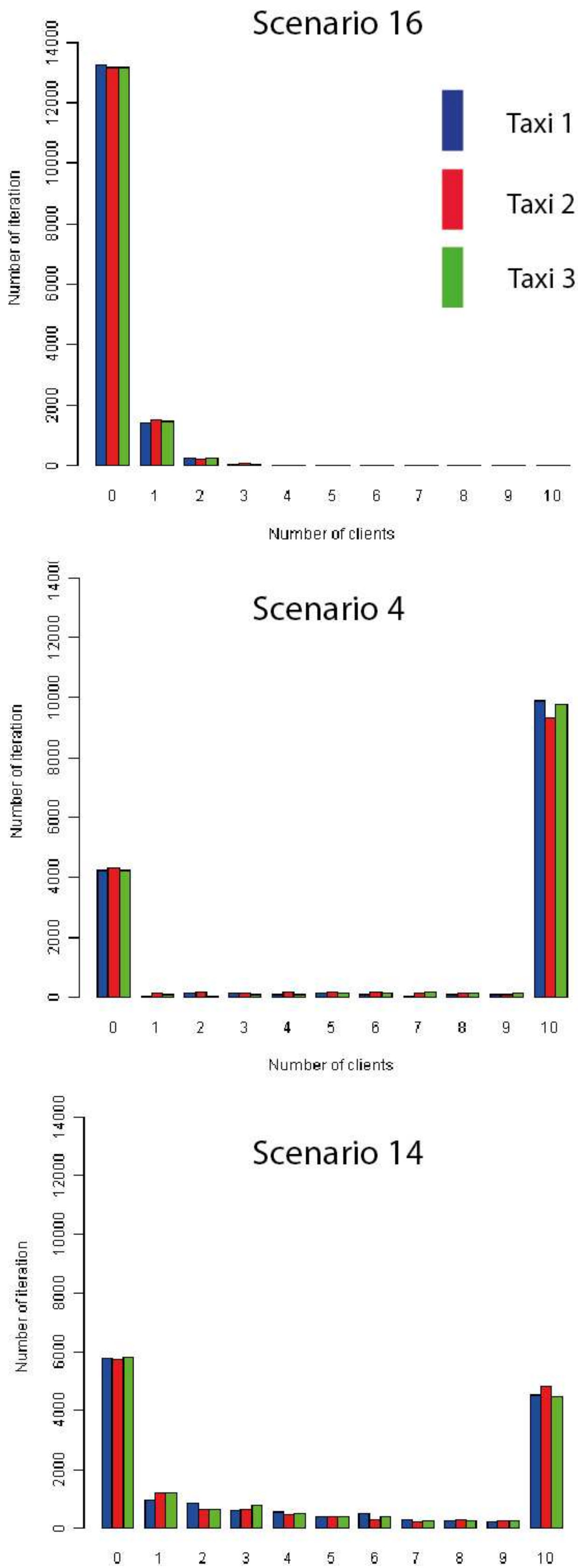


The clients-station rate is easier to analyze, because it depends on the number of clients generated along the simulation. The best results (corresponding to the lowest rate) are obtained in the scenarios which frequently generate little groups of clients. In this case, taxis can easily carry most of the clients. The best rate obtained is around 5% (scenario 23). The worst cas of clients-station rate is above 90% (scenario 15): too many clients are generated during the simulation. In such a configuration, taxis cannot empty the stations and we can conclude that the system is completely saturated.

About the taxi occupancy rate, we detected three forms of distributions, characterized by the number of generated clients (fig. 8). The first one shows a clear peak in the first class of occupancy rate (close to 0%), occurring each time the client density is too low. In this particular case, most of time taxis are empty. In the best configurations, they only carry 2 clients. It happens when the time granularity is loose or when the number of clients is not sufficient (e.g. scenario 16). However, these simulations obtain better results in terms of servicing and clients-station rates.

A second kind of distribution enhances two opposite peaks (respectively at the lowest and highest occupancy rates, and between those, a slow decrease of values). This has often been observed for many previous simulations. It corresponds to an intermediate efficiency case (e.g. scenario 14).
Finally, a third distribution stands at the opposite of the first case, where a peak in the highest occupancy rate is noticeable. In this case, the client density is rather high and taxis do not need to drive a lot to get new clients. When they arrive at a station, they directly fill their vehicle and go to the market. This process is repeated during all the simulations and unfortunately provides a very limited exploration of the geographical space. However, these simulated scenarios do not correspond to the most efficient services, due to the global system saturation we already explained.

Figure 8: Three different observed shapes in the occupation rate distributions (number of iterations is equal to statistical frequency)



Another interesting observation is the similar occupancy rate in some distributions illustrated by the figure 9. Indeed, there seems to be a specific ratio between time granularity (client generation frequency) divided by scale (quantity of clients). For instance, a ratio of 1 or 2 between these two parameters generally induces a bimodal distribution of equivalent occupancy rate (P_0=P_{10}). Beyond, when this ration is around 5 or 10, the transport efficiency allows very good grouping in the vehicles (P_0<P_{10}). All the other cases (with generation frequency / number of clients less than 1) correspond to a lower efficiency in terms of occupancy rate (generally (P_0>P_{10}), because the taxis often travel with available seats. This means the relation between the number of clients and their generation frequency is an important criterion in finding an optimal service configuration. This conveys a good correspondence between the fleet capacity and the transportation demand, whatever the network shape.

Figure 9: Comparison of taxi occupancy rates. 0 identifies the peak of travels without any clients in the taxi (P_0), 10 corresponds to a peak of frequency with 10 clients (P_{10}), P_0>P_{10} means that there is more frequently no client in the vehicle than 10 clients (in average), P_0<P_{10} tells the opposite, P_0=P_{10} means that the two peaks are somewhat similar.

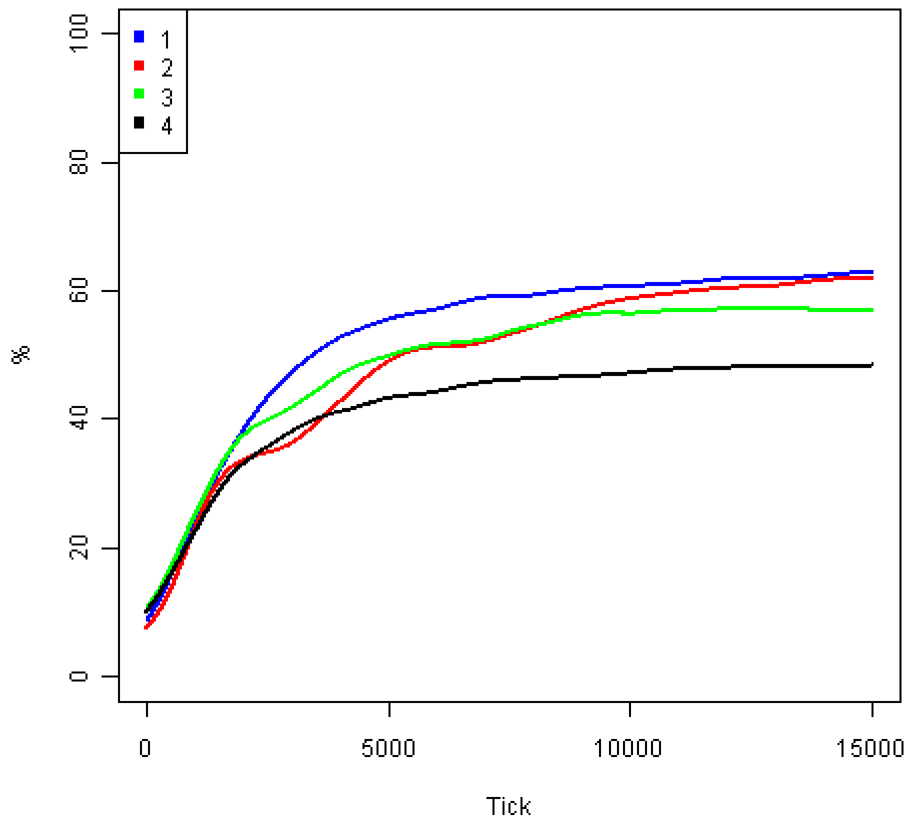
Scenarios	Number of clients	Frequency	1	2	3	4
1	5	5				
2	5	10				
3	5	20				
4	5	50				
5	50	5				
6	50	10				
7	50	20				
8	50	50				
9	100	5	**			
10	100	10				
11	100	20				
12	100	50				
13	100	100				
14	100	200				
15	100	500				
16	250	5	**			
17	250	10				
18	250	20				
19	250	50				
20	250	100				
21	250	200				
22	250	500				
23	500	5				
24	500	10	**			
25	500	20				
26	500	50				
27	500	100				
28	500	200				
29	500	500				
30	500	1000				
31	500	1500				

	Occupancy rate with P_0>P_{10}
	Occupancy rate withP_0=P_{10}
	Occupancy rate with P_0<P_{10}
**	Important diffrence between taxis

4.2. Influence of the network on transportation efficiency

We can observe that the network form influences the service efficiency in a certain way. The resulting differences are not very visible for the three realistic networks. That depicts three spatial structures supposed to be typical in terms of market locations and topology structure. This means the randomness of the operating system permits to easily adapt to any network configuration and spatial distribution of client demand. Moreover, some variations in the efficiency due to the network structure appear obvious. The most visible differences concern the (4^{th}) rectilinear network (fig. 10), which reduces the connectivity to explore the territory to serve in the best way, due to arcs shape. This rectilinear network is often less performing than the others, especially regarding the servicing and clients-station rates, in any of the simulated configurations, sometimes with noticeable differences (about 20%). This means that the topological structure plays a non negligible role in the capacity of a given service to efficiently operate. This factor seems to have more influence than any change in the demand or places of interest locations (cases of the 3 'realistic' networks).

Figure 10: Servicing rates for the scenario 21 (4 spatial configurations)



The comparison between the 4 spatial configurations as depicted in the figure 10 shows that:

- for the 3 random configurations (networks 1, 2 and 3), there is almost no difference in convergence ; agent randomness is probably the explanation;
- But the network 4 has a lower servicing rate 2 which seems more restricting for agents because it impairs the shortest path efficiency.

In the figure 11, we use the servicing rate to classify the simulations on the whole networks. In complement (figure 12), we process the deviation between the best and the worst simulations of the servicing rate, the worst simulation always being the one of the network 4.

Figure 11. Classification of the simulations according to the average servicing rate for the 4 networks (for instance, S21 of figure 9 belongs to the second class [40;60[of servicing rate)

Number of clients created \ Frequency (iteration)	5	50	100	250	500
5	S1	S5	S9	S16	S23
10	S2	S6	S10	S17	S24
20	S3	S7	S11	S18	S25
50	S4	S8	S12	S19	S26
100			S13	S20	S27
200			S14	S21	S28
500			S15	S22	S29
1000					S30
1500					S31

[0;40[	[40;60[	[60;100]

Figure 12. Classification of the simulations according to the deviations between the worst and the best servicing rates obtained (for instance, S21 of the figure 9 belongs to the second class [8-16[of deviations)

Number of clients created \ Frequency (iteration)	5	50	100	250	500
5	S1	S5	S9	S16	S23
10	S2	S6	S10	S17	S24
20	S3	S7	S11	S18	S25
50	S4	S8	S12	S19	S26
100			S13	S20	S27
200			S14	S21	S28
500			S15	S22	S29
1000					S30
1500					S31

[0;8[	[8;16[	[16;32]

From these figures and simulations, we can get a few interesting results. Firstly, the simulations with the lowest deviations involve two distinct "extreme" cases. In saturated situation taxis do not succeed in manage too many clients. We conclude that these critical situations are not valid for studying the network influence. Secondly, let us notice that all the simulations with valuable servicing rates are rather close to each others and generally belong to the middle class of the classification, except the simulations S7 and S12 (for those, the network 4 obtains a worse servicing rate value). This confirms the fact that the network 4 is less efficient than the other networks. Thirdly, intermediate simulations between ideal and critical conditions globally show important deviations of servicing rates (i.e. a large variability). At the opposite, client density is so weak that taxis remain almost empty and any cooperation becomes useless, whatever the simulated networks.

By comparing these two figures 10 and 11, we can conclude that:

- whatever the network shape (fig. 6), networks created randomly have a low influence on the system performance;
- the Manhattan network implies a certain agent behavior: taxis reach less easily the targeted stops on such a rectilinear network;
- this study enables to define a range for optimal conditions according to two parameters (iteration frequency and number of generated clients) to simulate our model, which correspond to a set of configurations (s5, s6, s9, s10, s11, s18, s19, s20, s26, s27, s28), all having ratio between the two parameters more or less similar.

5. Conclusion and discussion

This paper provides some methodological propositions for a robust validation of a transport system model. It is a first step progress in transport model robustness assessment using ABM. The first results seem promising. The robustness analysis is fruitful and show that it is possible to get transport efficiency improvement thanks to a set of weakly cognitive co-operating agents in a random exploration environment. However, an important part of this efficiency is included in a few determinant parameters. Indeed, there somehow exists an optimal ratio for a good service efficiency between the vehicle fleet and the client time-space density. This optimal ratio depends on the territory to serve, described by its topological network structure. Thus, this papers deals with a complex methodological issue composed of three interacting dimensions: the *scalability*, tested with regular increase of generated clients, the *space-time granularity*, represented by the frequency of these generations, and the *space effect*, realized by a few specific topological networks.

In terms of transport outcoming contribution, this work, even theoretical, shows that it is convenient, using a short sensitivity analysis process, to figure out some threshold values in transport efficiency. Those thresholds can significantly vary according to the service configuration. It is indeed quite difficult to state whether or not a flexible transport is efficient without considering all its parameters, and tuning them on their whole validity interval(s). It takes a long time to perform these kinds of analysis (many clients generated and many scenarios of simulation), but it seems to us a relevant way to test the system robustness and to clearly set the influences from some key parameters through the model behaviour.

More precisely, studying the different efficiency rates show that some configurations frequently have good efficiencies on both criteria (fig. 12). In middle condition simulations, it is then enabled to determine which configurations reach the best rates, providing a kind of optimal liberty space for the taxis to operate. This space would be the one in which the proposed service fits the best way to the environment requirements (clients demand, market locations, network structure). This is our point of view for considering the model validation. Further simulations and parameter variations, including peculiar territories and networks, should allow us to provide an overview of our virtual flexible transport behavior, in terms of efficiency and robustness.

When can a model be finally validated? Considering our case study, we can argue that model validation must be done according to the studied complex systems and the scientific question. Verification is often assimilated as a formal proof of the model by using predicates written within a formal algebra. Contrary to model verification, model validation seems to us that experience, data knowledge of the complex system, combined to suitable statistical clues such as the ones we proposed in this paper, are probably the keys for a successful validation process.

Introducing expert experience of the domain in the validation process leads to define an interactive interface that drives the model exploration. In our case, domain experts have directly participated in the modelling process. The model has been both assessed through a set of quantified parameters and a simple visualization analysis (like a dynamic map). It allows us to reduce the number of simulations necessary to be computed while ensuring a suitable model analysis. Also it permits to keep a low validation cost and to give confidence in the validation process, due to an interdisciplinary team joining computer scientists and geographers who cooperate in the field of geomatics applied to transportation for a long time. The next step of this research is to simulate real networks and possible flexible transport servicing for planning decision help.

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